Automated Wheat Disease Classification Under Controlled and Uncontrolled Image Acquisition

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Abstract. This paper presents a practical classification system for recognising diseased wheat leaves and consists of a number of components. Pre-processing is performed to adjust the orientation of the primary leaf in the image using a Fourier Transform. A Wavelet Transform is then applied to partially remove low frequency information or background in the image. Subsequently, the diseased regions of the primary leaf are segmented out as blobs using Otsu's thresholding. The disease blobs are normalised and then radially partitioned into sub-regions (using a Radial Pyramid) representing radial development of many diseases. Finally, global features are computed for different pyramid layers and combined to create a feature descriptor for training a linear SVM classifier. The system is evaluated by classifying three types of wheat leaf disease: non-diseased, Yellow Rust and Septoria. The classification accuracies are slightly over 95% and 79% for images captured under controlled and uncontrolled conditions, respectively.

Keywords: Wheat disease recognition, radial pyramid, rotation using Fourier

1 Introduction

With the rapid development of technologies for camera devices, especially on smartphones, the use of image processing algorithms now play an important role for a number of applications; for example, face and object recognition and biomedical applications are important topics in computer vision. Another application area which could benefit significantly from the use of image processing techniques is that of agriculture. For example, plant disease can cause serious damage with regard to the loss of agricultural products and can thus contribute to the problems of world economy and human health. This paper proposes an automated classification system for preliminary recognition of different wheat diseases to assist farmers in crop management (example images can be seen later in Fig. **2**). Our study is initially focused on three commonly seen types of foliar wheat disease, which differ in visual appearance [1]. The paper is divided into four main sections. Literature review is detailed in Section 2. Section 3 explains the details of the proposed system. The experimentation and results are discussed in Section 4. Finally conclusions are presented in Section 5.

2 Literature Review

In machine vision Histogram of Oriented Gradients (HOG) and Scale-Invariant Feature Transform (SIFT) algorithms have been shown to be potential local feature descriptors, especially for object classification or detection. Considering the challenges of computer vision for a plant pathology application, disease shapes or distribution patterns can appear differently within the same type of disease depending on their severity levels. Additionally, the colours and the distributions can exhibit similarly but with slight differences between different types of diseases. Other challenges generally include the effects of illumination change and background clutter.

The use of imaging techniques in plant pathology applications has been conducted over the past decade. In 2003, El-Helly et al. [2] implemented Fuzzy c-means to segment diseases from a leaf and then applied various shape characteristics, such as principal axis length, eccentricity, and compactness on three types of cucumber diseases. Amongst the studies in this area, the combination of global colour, texture and shape features are the most frequently applied features which have been shown to be accurate in classifying various diseases [3, 4]. Camargo and Smith [3] applied this combination of features in a multiclass SVM classifier to identify three types of cotton disease. Although the feature combination considers global properties of an interesting area, to use all features from each feature set is time consuming and can also decrease the classification accuracy (over-fitting). Combinations of features within each feature set were investigated in our previous work [5] to ensure that a selected feature subset contributes significant information representing disease/non-disease area. Moreover, most of the recent studies initially experimented on several diseases whose images were acquired under controlled conditions or required a manual process to reduce the effect of the background. This paper proposes a practical system that is partially tolerant to background clutter and changes in lighting conditions using previously selected feature sets and an extended version of the features which models how a disease develops.

3 Methodology and Proposed Classification System

Our proposed system is illustrated in Fig. 1 and consists of four main components: pre-processing, segmentation, feature extraction and classification. Images are initially scaled and rotated to standardise image size and to adjust the leaf orientation for consistency. Then the background is partially removed and diseased regions are extracted from the leaf during the segmentation process. Each disease region is normalised to a square patch representing a disease texton. Inspired by the Spatial Pyramid method [6] which divided an image into sub-regions for different levels, our disease texton is radially partitioned into layers for different levels regarding the natural characteristics of diseases. Then global features based on texture, colour and visual perception are calculated for sub-regions of the radial pyramid. Finally, the features are combined to create a feature descriptor which is later used as an input for training a multiclass SVM model. Details of the processes are described below.

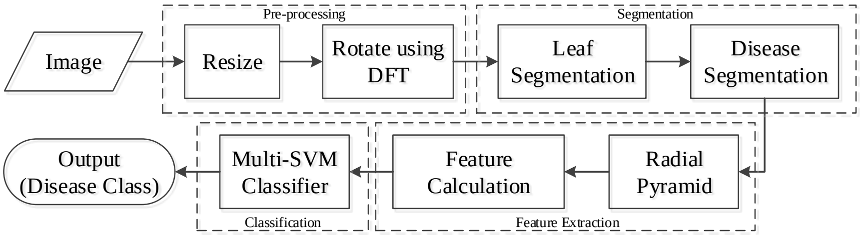


Fig. 1. Our proposed system for wheat disease classification

3.1 Leaf rotation using discrete Fourier transform

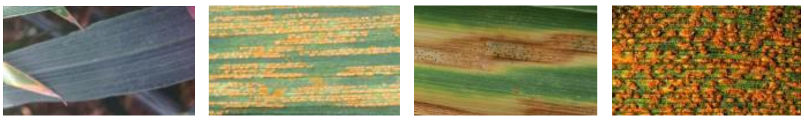
Firstly, we calculate the image gradient using a Canny edge detector to provide information on the alignment of the leaf and leaf veins; this operator is also reasonably invariant to different light conditions. Then, a two-dimensional discrete Fourier transform (DFT) is applied to compute major frequency components in the edge image. The Fourier spectrum shows a major dominant line that is orthogonal to the leaf orientation, and the computed direction of the line is used to determine the rotation required for leaf alignment (see example in Fig. 4(b)). The approach is also robust to rotate leaves that reside in a cluttered background.

3.2 Leaf segmentation using multi-resolution discrete Wavelet transform

A single-level two-dimensional Wavelet transform (DWT) is exploited to decompose an image into coefficients of four different components, an approximation component (cA), horizontal, vertical, and diagonal details (cH, cV, and cD). We combined horizontal, vertical and diagonal detail information based on Daubechies wavelets and then thresholded the low coefficient values out to remove part of the background from consideration in the subsequent stages of our process (see Fig. 4 (d)).

3.3 Disease Segmentation using Otsu's threshold

Provided that the non-disease area is consistently greenish, Otsu's threshold is used to maximize between-class variance of the diseased leaf to segment out the disease regions. However, to eliminate the effects of lighting conditions we empirically selected thresholds from Cb and Cr colour components.



(a) Non-disease (b) Yellow rust (c) Septoria (d) Leaf rust

Fig. 2. Nature of different diseases

3.4 Feature Extraction

Radial Pyramid. Our radial Pyramid is inspired by a spatial pyramid, an extended version of local feature descriptors such as SIFT for scene classification (Lazebnik et al. [6]). The radial pyramid structure aligns with the typical radial development of many diseases. The Septoria disease develops from a small brown-spot surrounded by a yellow halo; yellow rust disease (stripe rust) usually develops on leaf veins; leaf rust usually has a brown or yellow circular shape [1].
Fig. **2** displays examples of different wheat diseases exhibiting different characteristics.

Assuming we have segmented disease blobs from the previous stages of our process these blobs are normalized into square patches or disease textons [7] representing fundamental disease structures. Two types of texton normalization are explored. A nearest neighbour method is used to normalize a patch with a selection of the nearest neighbouring pixels alternating to maintain the disease scale or to scale a texton into a square patch; eleven normalized patches using this approach are illustrated in Fig. 4(f). Another one is a bicubic normalization method which creates a patch by averaging the neighbouring pixels giving a smoother texture in the patch.
Global Feature Descriptor. We deployed three different types of features based on textures, colours and visual perception investigated in [5]. Textural features (F_H) is developed through a spatial grey-level matrix [8]. Colour features (F_C) are based on statistical information of each disease patch, such as mean, variance, skewness and kurtosis of a colour component distribution. Lastly, Tamura [9] proposed a set of features (F_T) describing image patterns more visually, such as coarseness, contrast and directionality. These features are calculated for each level (k) and layer (l) of a radial pyramid (see Fig. 3 and disease examples in Fig. 4(i-l)). A final feature descriptor (F_L) is constructed from a combination of features from each level. Feature descriptors are created by the concatenation in (1) and (2).

$$F(k,l) = [F_H(k,l)\ \ F_C(k,l)\ \ F_T(\mathrm{k},\mathrm{l})] \quad (1)$$

$$F_L = [F(1,1)\ \ F(2,1)\ \ F(2,2) \ldots\ F(L,1) \ldots F(L,L)] \quad (2)$$

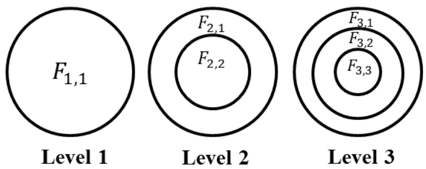


Fig. 3. Example of three-level radial pyramid. There are 1, 2 and 3 layers for levels 1, 2 and 3.

3.5 Multiclass SVM classification

In order to create a practical application, we selected SVM as our classifier as it has been shown to obtain high accuracy, good generalisation and computational efficiency compared to k-NN or neural network-based classifiers. In the learning phase, all created disease textons are trained for a linear SVM classifier. Assuming that all the patches are equally important, the output class of the image is the group that has the most frequently displayed results from the classified textons.

4 Experimentation and Results

We experimented with two types of datasets: data obtained under controlled conditions and uncontrolled conditions. Each dataset contains three types of wheat leaf (50 images each for non-disease, yellow rust and Septoria diseases). The controlled data were obtained from the Food and Environmental Research Agency (FERA [5]) and the leaves are manually segmented out from the background before being used as inputs for the system. Uncontrolled data (Internet) were obtained from online open sources that were collected from different farms and at different times using different capture devices, providing various illumination effects and colour tones. Additionally these images are also challenging due to background clutter and different image resolutions.

The system was evaluated using MATLAB 2014b. During pre-processing, the images are resized to 300x300 pixels. Four radial pyramid levels and four different patch sizes (15, 20, 25, and 30) are investigated in the experimentation. The colour representation was empirically selected as the YCbCr colour space. The testing scheme is based on 5-fold cross-validation testing.

The results are summarised in Table 1 and are compared with our previous work [5] which used the controlled data only (FERA) and applied sets of global features on the whole image only. The classification accuracies show improvements to 95.73% and 95.5% for 1-level and 4-level pyramids, respectively. Considering the uncontrolled data (Internet), the previous system obtained classification accuracy of 72.67%. Including rotation and segmentation from this paper, the results rise to 80.13%. Nevertheless, our system with 4-level pyramid produces a little lower accuracy at 79%. The investigation shows that the effect of the remaining background from the segmentation phase has an impact in creating accurate disease textons, especially for non-disease patches, most of which are built from the background.

Table 1. Classification accuracies of the proposed system compared to our previous work [5]

Dataset	Feature	Accuracy (%)
FERA	Top Textural Features [5] (rectangular rotation)	91.87
	Top Textural Features with DFT rotation	88.80
	Top Textural Features with DFT rotation and pyramid level = 1	**95.73**
	Top Textural Features with DFT rotation and pyramid level = 4	**95.50**
Internet	Top Textural Features [5]	72.67
	Top Textural Features with DFT rotation and segmentation	**80.13**
	Top Textural Features with DFT rotation, segmentation and pyramid level = 3	78.27
	Top Textural Features with DFT rotation, segmentation and pyramid level = 4	**79.00**

5 Conclusion

A practical classification system is proposed for classifying three types of wheat diseases. Leaf rotation is achieved by using a Fourier transform, and a two-dimensional Wavelet transform is used to partially remove low frequencies or background. A Radial Pyramid, an extended version of global feature descriptors, is established to model the nature of disease development. We have demonstrated the robustness of our system using controlled and uncontrolled images and the classification accuracies obtained show that this initial system can be implemented as a real application for detecting wheat diseases.

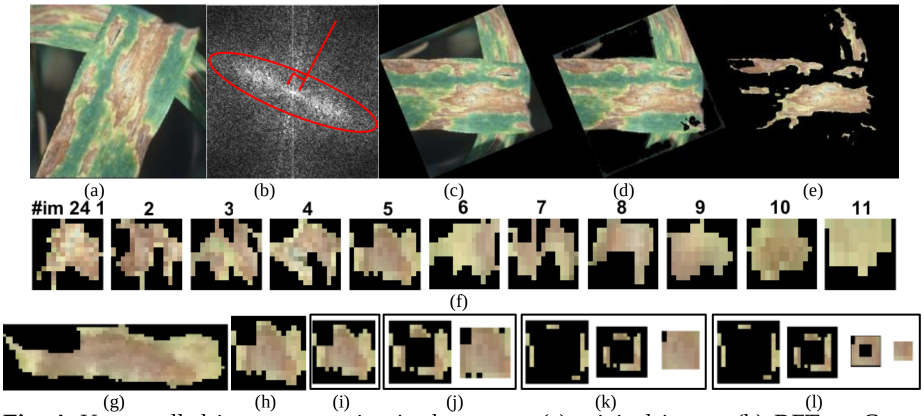


Fig. 4. Uncontrolled image processing in the system (a) original image, (b) DFT on Canny edge, (c) rotated image, (d) partially segmented image, (e) segmented disease, (f) constructed disease patches, (g) original disease blob (#5), (h) normalised disease patch (i) 1-level (j) 2-level (k) 3-level (l) 4-level radial pyramid patches

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